HARVIST: A System for Agricultural and Weather Studies Using Advanced Statistical Methods

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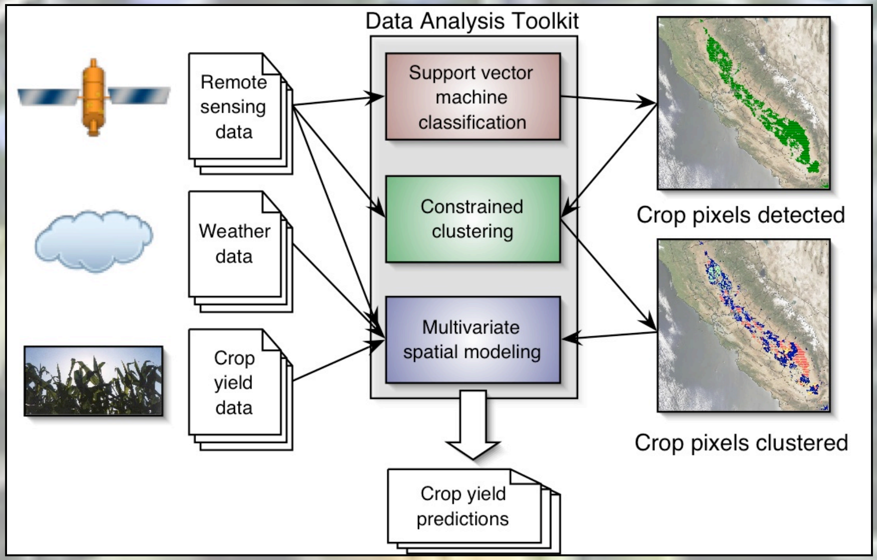
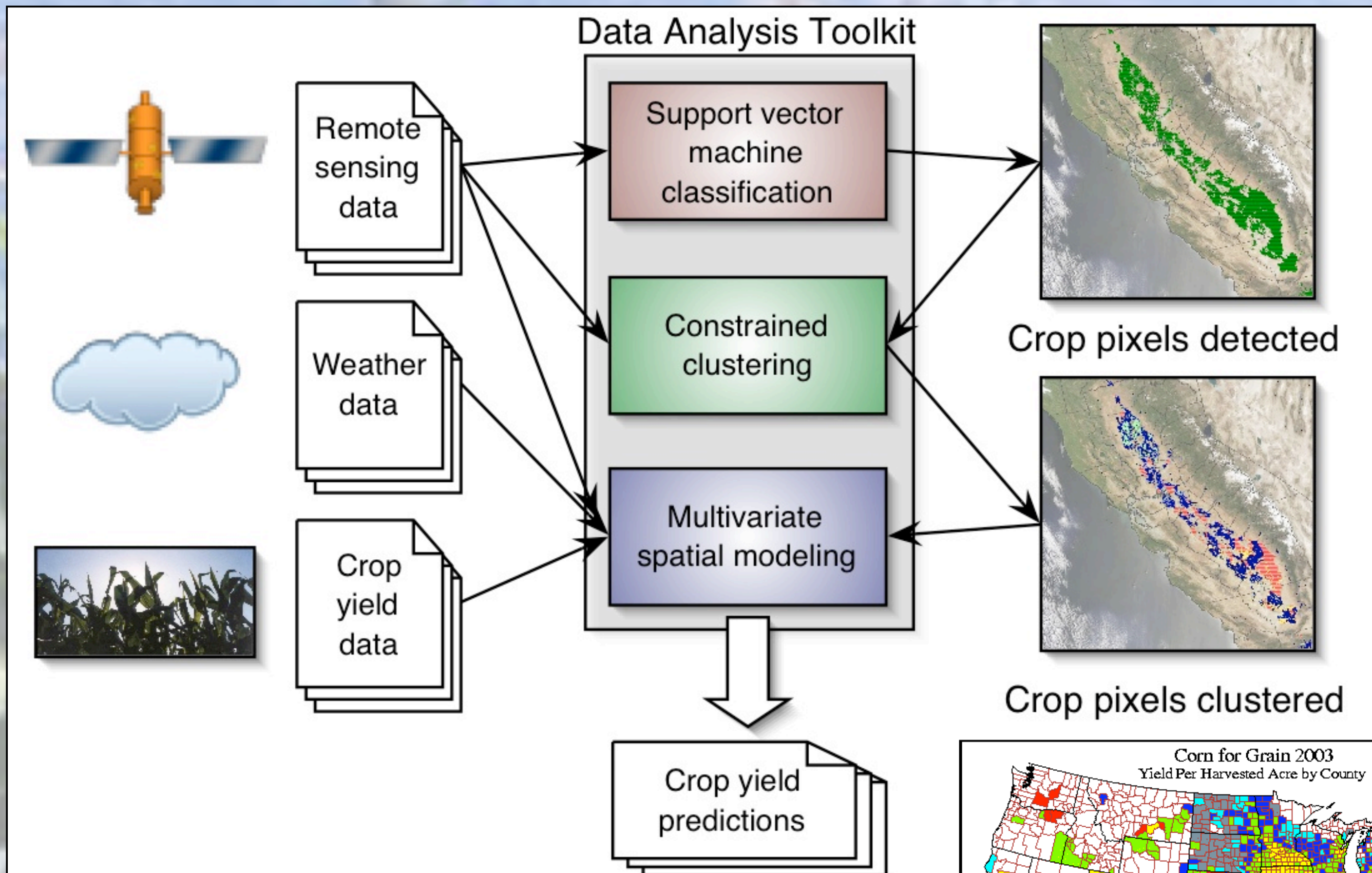
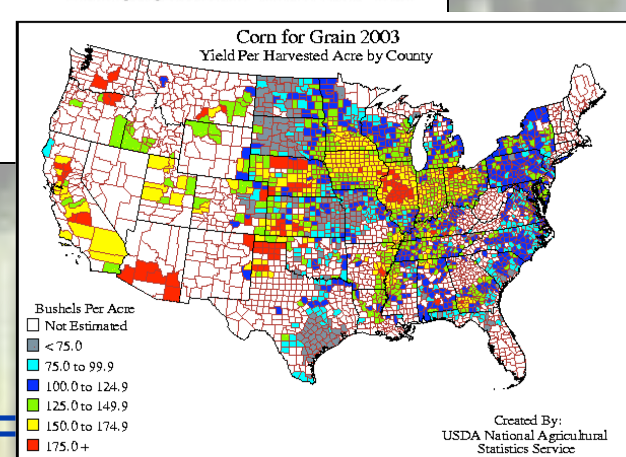


Outline

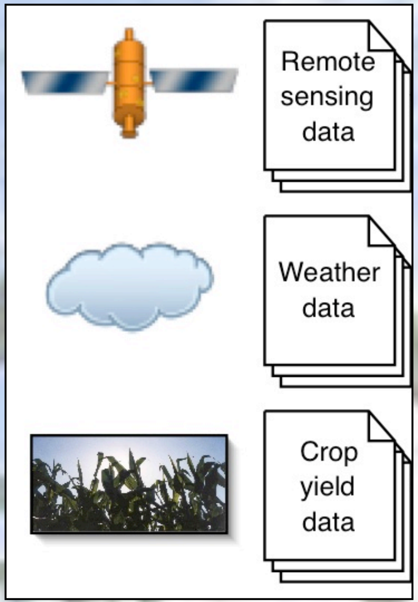
- Project overview
- Preliminary study: corn yield prediction (12 counties)
  – Key finding: integrating data from multiple sources increases prediction accuracy
- HARVIST demonstration
- Accomplishments
  1. Classifier method (SVM) efficiency improvements
  2. Integration of classification and clustering together
     - Example: only cluster regions known to contain vegetation
- Future plans

HARVIST Overview





Key Ideas of the Project

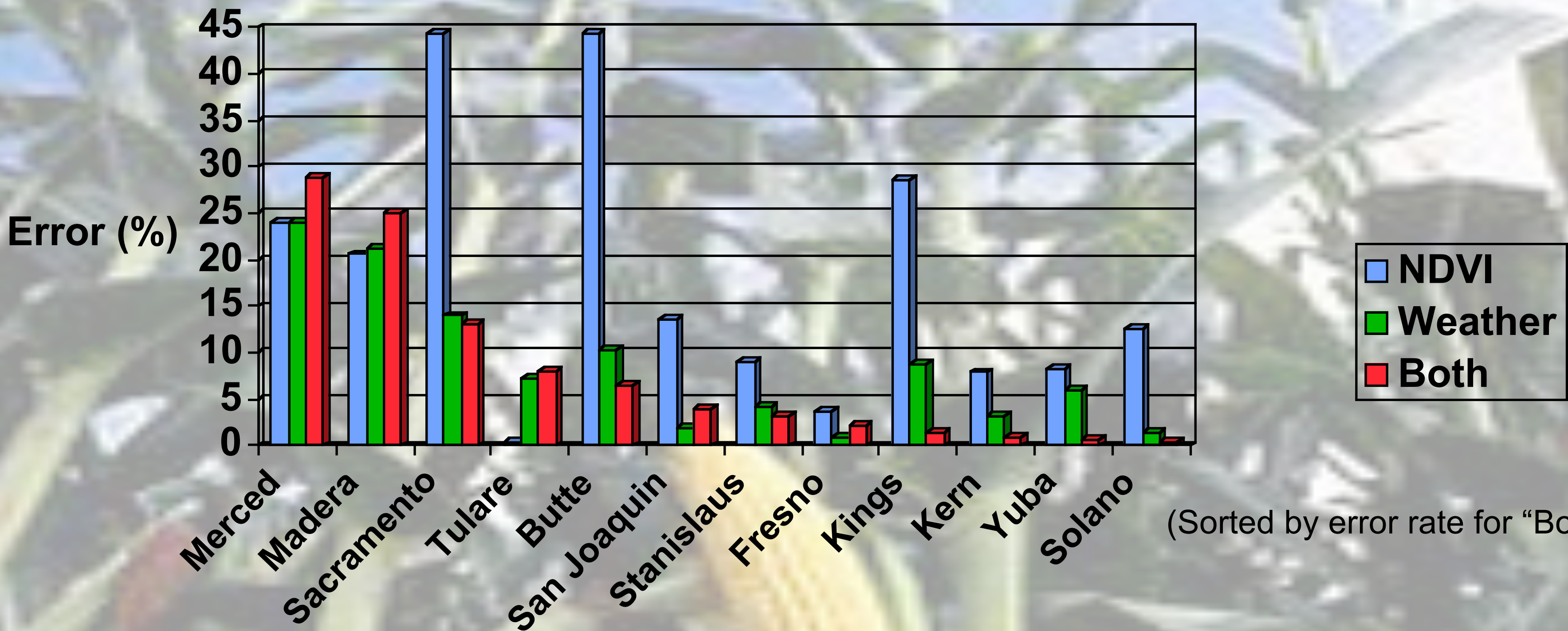


- Combine data from **multiple, diverse sources**:
  - Satellite imagery (LandSat, MODIS, MISR)
  - Weather stations (NCDC)
  - Historical crop yields (USDA)
  - Land cover types (USGS)
  - All at different spatial and temporal resolutions
- Optimize **machine learning techniques for image data**
  - Exploit spatial dependencies to improve efficiency
- **Analyze connections** between weather and agriculture
  - Learn relationships between variables from multiple different data sources
  - Our study: Predict crop yield for different weather conditions

MODIS: MODerate resolution Imaging Spectroradiometer;
MISR: Multi-angle Imaging SpectroRadiometer

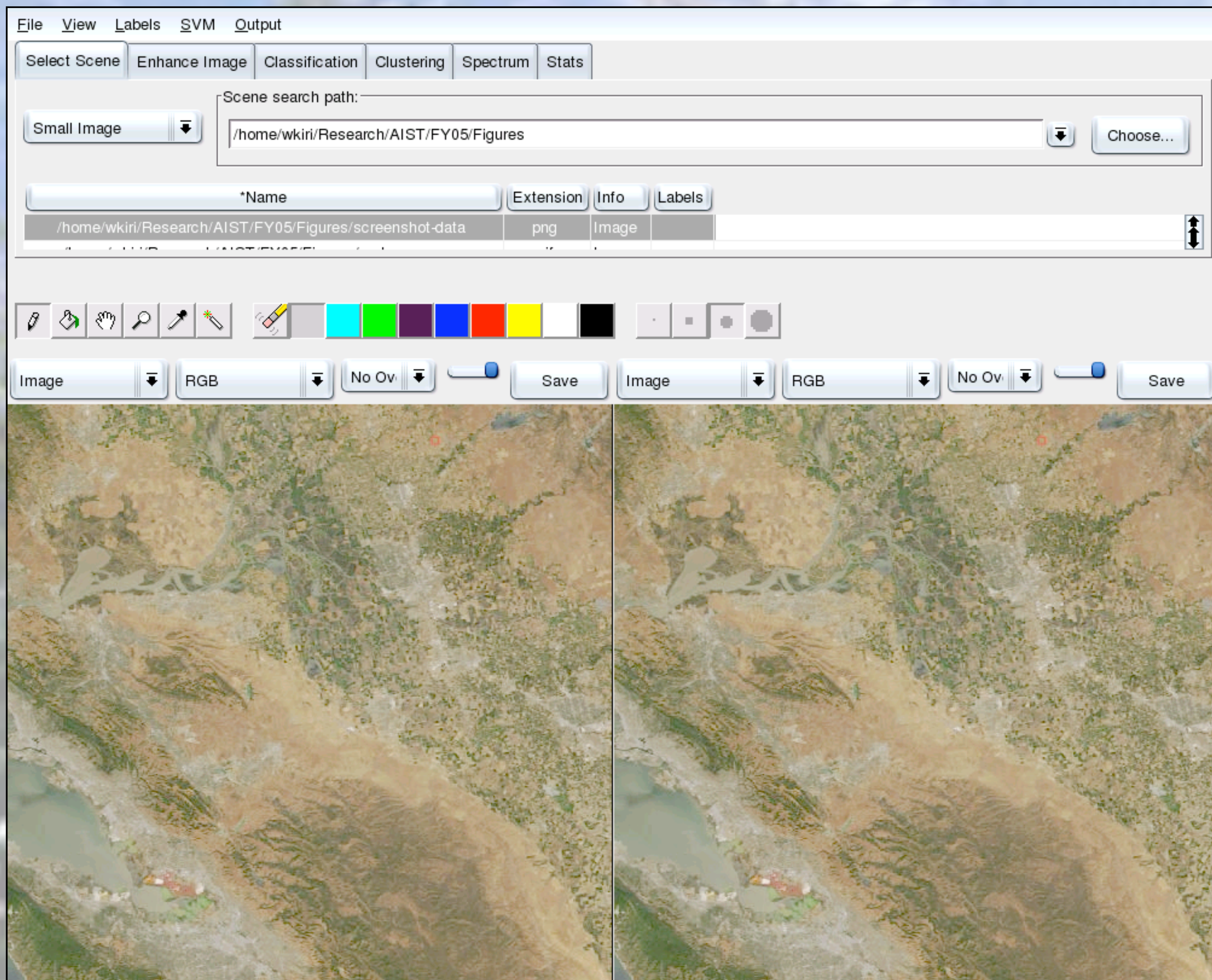
Preliminary Study: Corn Yield Prediction

- Goal: predict corn yield for 12 California counties
  - Train on data from 2002, 2003; predict for 2004
- Results:
  - Just remote sensing data (NDVI): 17.5% error rate
  - Just weather data (temperature and precipitation): 7.9%
  - Both: 7.0%



(Sorted by error rate for “Both”)

System Demo



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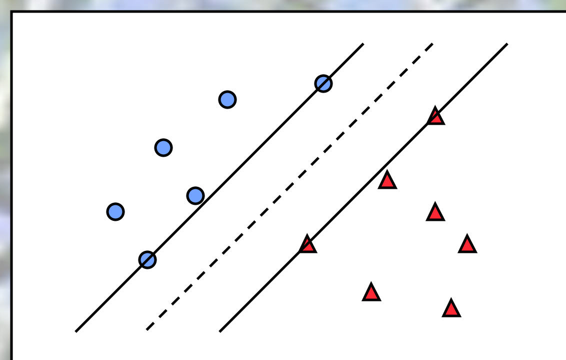
Featured Accomplishments

1. Classifier method (SVM) efficiency improvements

2. Integration of classification and clustering together
   – Example: only cluster regions known to contain vegetation

(1) SVM Efficiency Improvements

- Support Vector Machines (SVMs)
  - Identify a hyperplane that maximally separates pixels from each labeled class
  - Pixels on the boundaries are the “support vectors” (SVs)

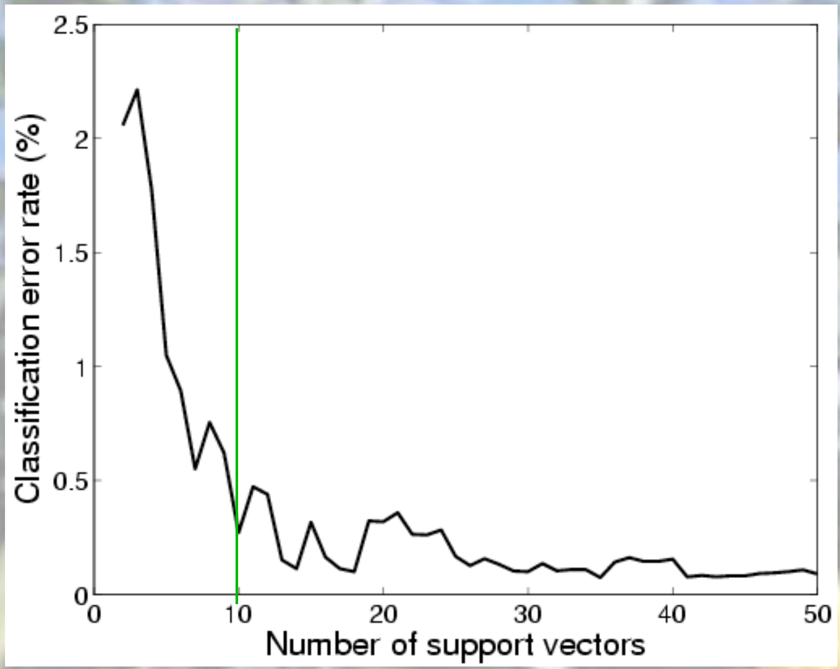


- Goal: reduce classification time (scales with number of SVs)
  - **Reduced Set** method: identify smaller set of SVs (~10x speedup, but pay pre-processing cost to find reduced set)
  - **Nearest Support Vector** method: adjust computation based on “difficulty” of item to be classified (~2x speedup)

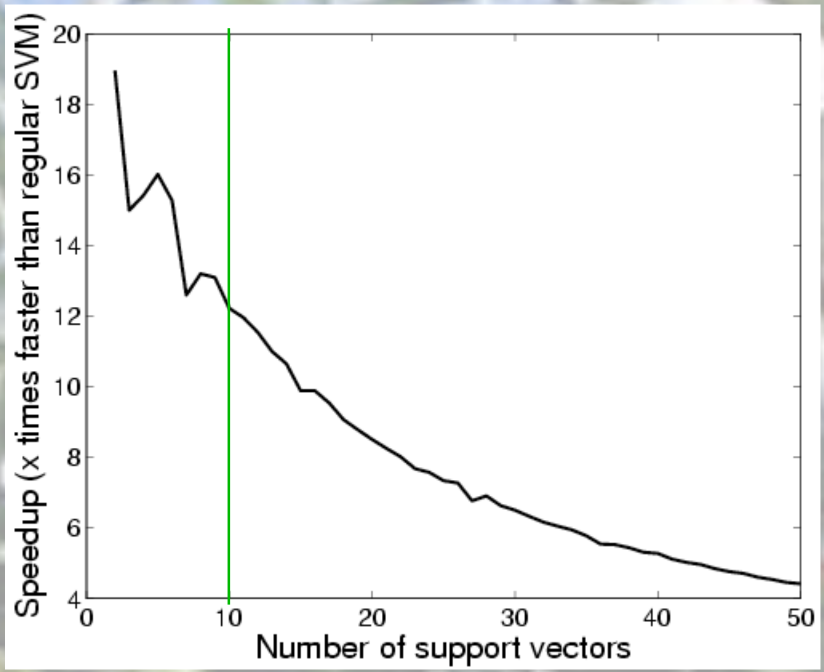
(1) SVM Efficiency Improvements: Results

- **Hybrid:** Nearest Support Vector + Reduced Set
- Tradeoff between accuracy and speed

Error rate



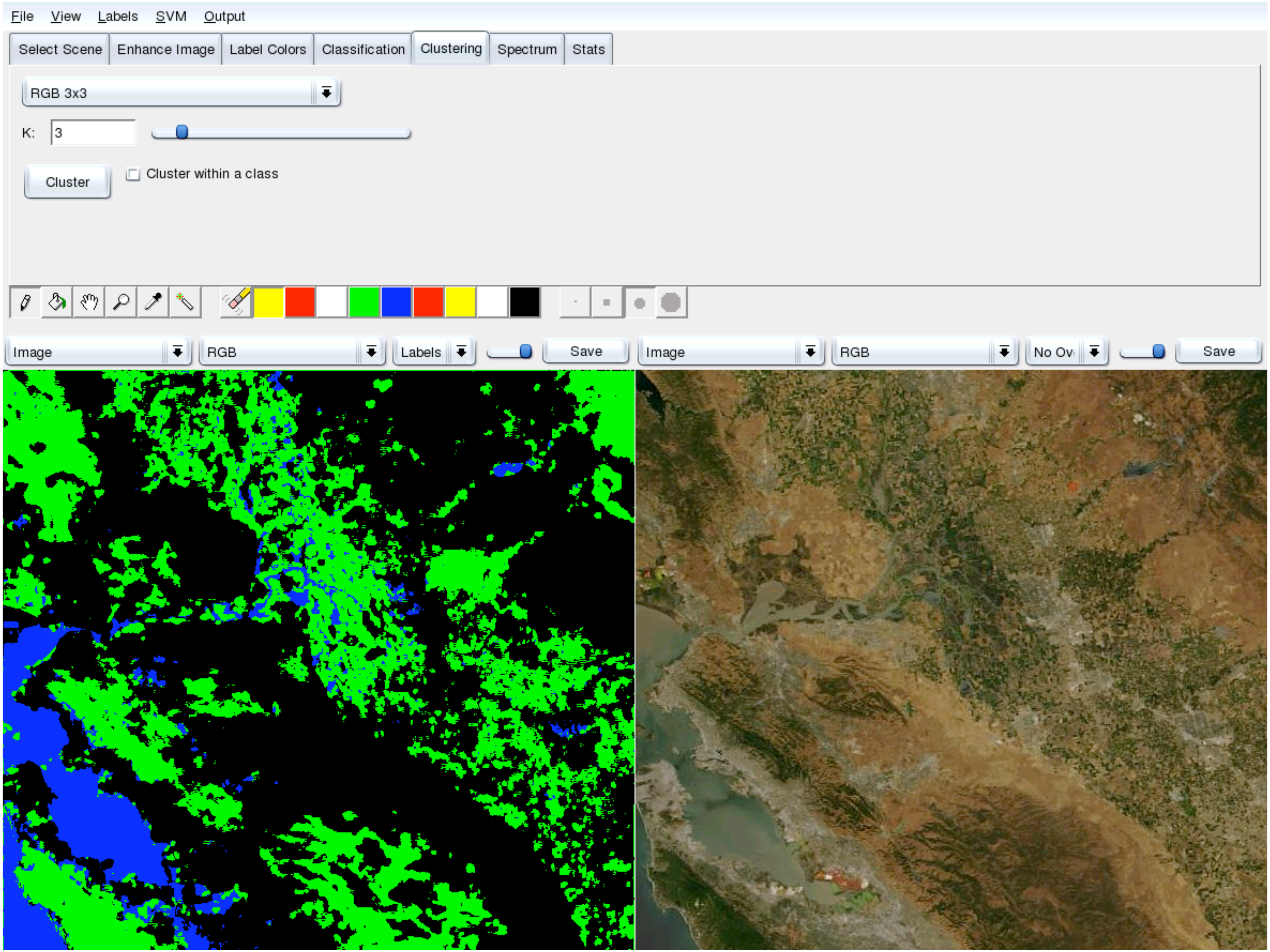
Speedup



(2) Integration of classification, clustering

- Idea: analysis methods share data and results

- **Example: clustering pixels from a specific class (focus of attention)**
  - User labels and classifies the image using an SVM, then identifies a specific class to be clustered
  - Enables further exploration of class structure
    - Motivation here: identifying meaningful sub-groups within a class where we can build specialized crop prediction models
    - Clustering also returns the “average” member of each cluster, to aid in interpretation of results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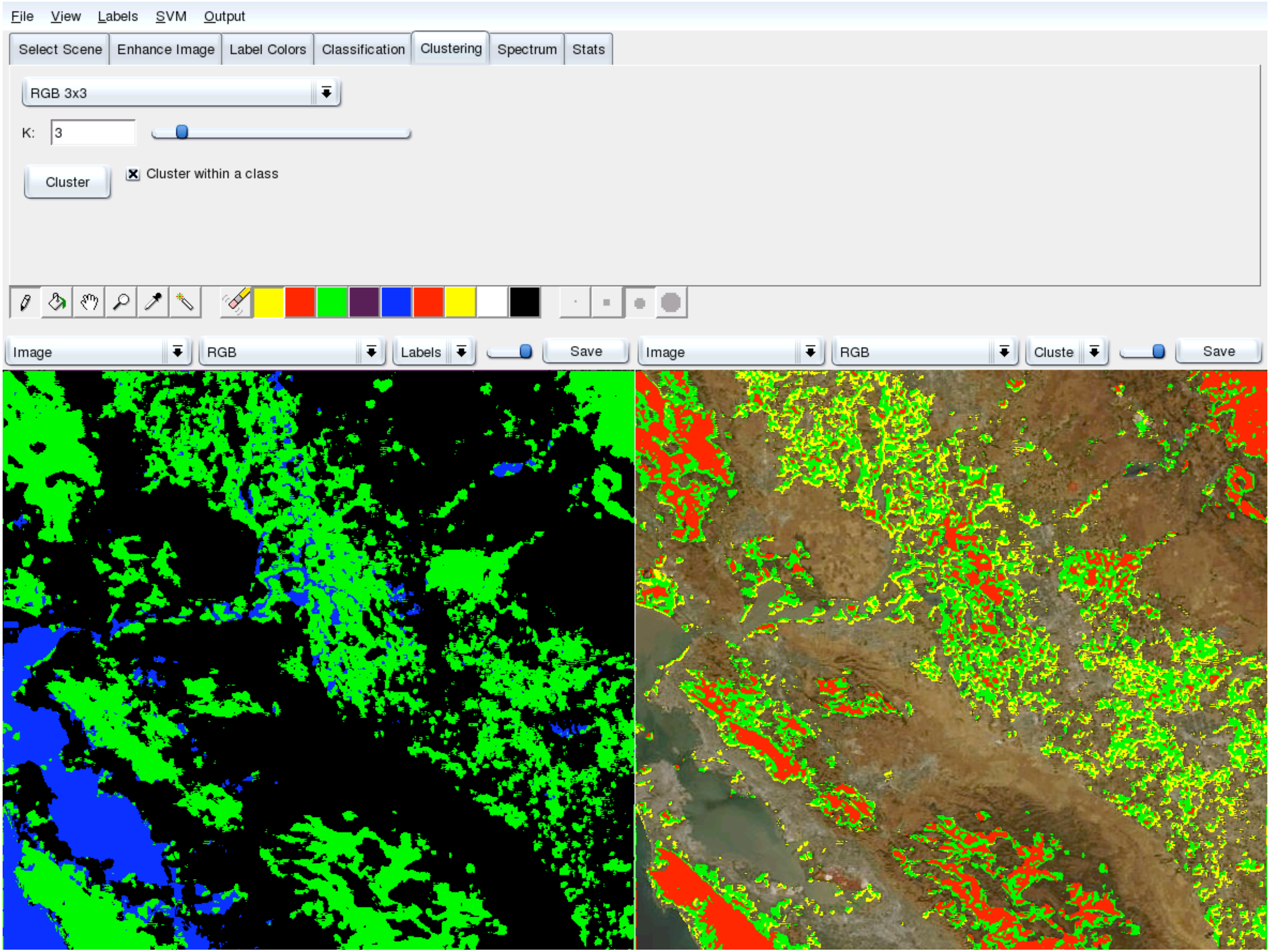
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Work In Progress

- Technology
  - Increase SVM, clustering **efficiency** further
    - Methods that leverage spatial relationships in the data
  - Conduct summer field study
    - Collect ground truth for different crop types in central California
    - Use this data to train a crop type classifier
    - Enables specialization of yield prediction by crop type
  - Add kriging/**interpolation** methods for to compensate for missing data or cloudy pixels
- Science
  - Analyze time series data from Kansas (105 counties) to identify **factors that impact high/low yield**
  - Integrate weather, soil properties data
    - Compare quality of predictions with and without these data sources

Long Term Goals and Benefits

- Produce a **single, integrated, graphical system** for classification, clustering, and prediction from multiple, **heterogeneous** data sources
- Demonstrate **global scalability** of enhanced SVM and clustering methods (optimized for image data)
- Demonstrate feasibility of system by **predicting crop yield** from remote sensing, weather, land cover, and soil type data bases